A/B Testing Team Project

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Executive Abstract

There is evidence to suggest that the emotional state of the presenter can have a significant impact on the learning outcomes of the audience[1]. For example, studies have shown that when a presenter is enthusiastic and engaging, it can increase the attention and motivation of the audience, leading to better learning outcomes. On the other hand, if a presenter is dull or uninterested, it can lead to reduced attention and motivation, resulting in poorer learning outcomes.

In addition, the emotional state of the presenter can also affect the way that information is processed and remembered. Research has shown that when a presenter is emotionally engaged, it can lead to better encoding of the information and improved memory for the material[2].

Our study tackles this interesting topic and investigates the causal effect of presenters' emotions on interest levels and learning outcomes, which can shed light on how educators can better present themselves and engage audiences to achieve desired educational success. Our experiment involved showing randomly sampled videos from a selected pool to participants and recording their quiz scores before and after watching the video. We also asked participants their interest levels towards the video content at the end. In the end, we were able to obtain 254 responses for our analysis. After initial data exploration, we run both plain regression and the regression that incorporates heterogeneous variables (gender, age, education) on various emotion features from videos. The result shows no significant effect for both regressions on all emotion features we run. Although the result is counterintuitive, we believe the limitation may stem within the limited dataset we got and indistinguishable emotion fluctuation in the video. However, our study still opens a world of possibilities for future studies by exploring a rich set of emotions. In the future, we will try to increase our dataset and improve the visibility of emotions in demonstration videos.

Introduction

Human's facial expression plays an important role in our daily life. From communication to making decisions, emotions always show clues on our facial expressions. In a TED talk, it

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[1] Tan, J., Mao, J., Jiang, Y., & Gao, M. (2021). The Influence of Academic Emotions on Learning Effects: A Systematic Review. International journal of environmental research and public health, 18(18), 9678. https://doi.org/10.3390/ijerph18189678
[2] Tyng, C. M., Amin, H. U., Saad, M. N. M., & Malik, A. S. (2017). The Influences of Emotion on Learning and Memory. Frontiers in psychology, 8, 1454. https://doi.org/10.3389/fpsyg.2017.01454

mentions that using facial expressions can increase the audience engagement and deliver the message more effectively[3]. Because humans express emotions via multiple ways, such as facial and vocal expressions, emotion coherence through those modalities can have significant effects on the perception and influence the audience attitude[4]. Therefore, investigating the causal effect of facial expressions to the interest of the audience is one of the interesting topics to explore.

In the past study, there are multiple papers talking about the effect of emotion on advertising engagement, or social media. However, there are only a few studies talking about the causal effect of emotion to the educational video.

In this research project, we want to study the effect of emotion on the presenter to the audience's interest and learning. In this experiment, we distribute a random sample of educational video to the audience. After watching the video, we ask the audience several questions as the baseline and develop a series of questions based on the baseline questions. Before the experiment, we try to collect the emotional data from the presenter in the educational videos, such as the level of smile (happiness), emotion neutrality, and sadness. Then we use several regression to find if there are any causal effects to the audience's interest and learning based on the audience's answers. The regression we plan in this project includes:

- The causal effect of emotion on the participants' self-reported interest scores
- The causal effect of emotion on the participants' post-quiz scores

The objective of this project is to try to see if there are any emotions that cause the audience to feel interested about the video. In the following part, we will first use the regression above to see separately the regression result in the empirical experimental setting, and since we believe causal effect might be different for participants of different gender, age, and education groups, we will also try to see the heterogeneous effect on these factors. Finally, we provide our conclusion for this experiment design.

Empirical Experimental Setting

Overview and Initial Exploration

For this experiment, we used a set of twenty-three videos explaining the basic concepts of A/B testing recorded by the students of the course A/B testing in Fall 2022 as our initial dataset. The videos are tagged with information about the gender of the presenter, the facial expressions of the presenter, and the emotion implied from the facial expressions. The tags are added using a facial analysis machine learning model.

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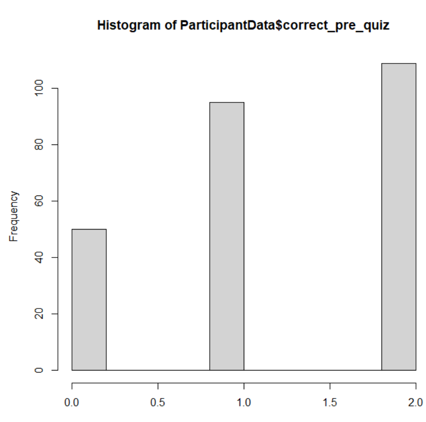
[3] C. Gallo. Talk like TED: the 9 public-speaking secrets of the world's top minds. St. Martin's Press, 2014.

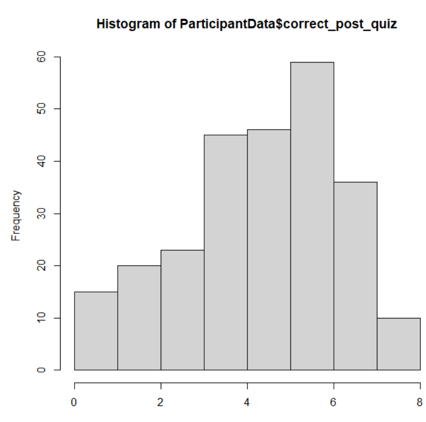
[4] C. Darwin and K. Lorenz. The Expression of the Emotions in Man and Animals. Phoenix Books. University of Chicago Press, 1965.

We used a survey platform to collect data of people watching the video. When a participant starts with the survey, they would first need to go through two pre-quiz questions, with the goal to test their knowledge of A/B testing before the experiment. Then, the participants would be shown one of the twenty-three videos. The video is decided randomly and the participant is not allowed to fast-forward or skip the video. After watching the video, they would first be asked how interesting and how boring they thought the video was, which are both measured on a 7-point Likert scale. Lastly, the participants would get a set of eight post-quiz questions, testing whether or not they actually understood the content of the video. By the end of the three-week collection period, we were able to collect data from 254 participants.

For the A/B test, we aim to find the causal effect of the facial expression and emotion of the presenter on the interest level and the post-quiz score of the participants. From the numerous fields of the facial analysis machine learning model tags, most notably, we picked the smile field (covariate *smile*) and neutral emotion (covariate *emot_neutral*) to represent the positive emotions while using the sadness field (covariate *emot_sadness*) to represent the negative emotions. The smile and sadness fields are considered the treatment of this study, and each *(video_id, participant_id)* pair is considered the unit of analysis. The intensity of the smile and sadness is determined using the facial analysis machine learning model mentioned above. Participants who are assigned videos with higher intensity of smile or higher intensity of sadness are considered the treatment group and the participants who are assigned videos with lower intensity of smile or lower intensity of sadness are considered the control group. Our aim is to see if the treatment group finds the videos more or less interesting (covariate *self_interest*) and if they have a higher or lower post-quiz score (covariate *correct_post_quiz*).

We first did an initial exploration on data obtained to better set up our experiment. A total of 241 observations out of the 253 are used as 13 participants watched videos where no faces were shown. Below is the distribution of the pre-quiz score and the post-quiz score. For the pre-quiz score, we can see that about 80% of the participants got at least one of the questions correct. As for the post-quiz score, the distribution is similar to a normal distribution where about 60% of the participants got a score between 4 and 6 and the highest and lowest performers are on either side of the dropping slope.





The distribution of the participants' gender, age, and education are shown below. As you could see, for all three demographics, the participants are pretty evenly divided into at least two groups. To calculate the heterogeneous causal effect on gender (covariate *demo_gender*), age (covariate *demo_age*), and education level (covariate *demo_education*), we grouped the participants into two groups for each of the traits. Specifically, for the gender field, we compared females versus all other gender categories. For the age field, we compared participants in the 18-24 age range with all other age groups. For education, we focused on participants with Bachelor's or lower degrees and those who have Master's or even higher degrees. Finally, we were able to get *gender_group*, *age_group*, and *education_group* indicators for our specific interest. These variables in each heterogeneous aspect are encoded as either 1 or 0 (see Appendix).

Age	Gender	Education
18-24: 92	Female: 99	Bachelor's degree or below: 116
25 or above: 149	Male and others: 142	Master's degree of above: 125

We also used a two-sided t-test to compare the means of the pre-quiz score between the groups divided using the demographic of participants. We could see that the pre-quiz score is similar for the groups divided using age and gender, but it is not as similar for the groups divided using education level.

Age	t = 0.41025, df = 235.16, p-value = 0.682 alternative hypothesis: true difference in means is not equal to 0 95 percent confidence interval: -0.1541597 0.2352483 sample estimates: mean of x mean of y 1.259843 1.219298
Gender	t = 0.15214, df = 206.64, p-value = 0.8792 alternative hypothesis: true difference in means is not equal to 0 95 percent confidence interval: -0.1805768 0.2107782 sample estimates: mean of x mean of y 1.250000 1.234899
Education	t = 1.3726, df = 238.59, p-value = 0.1712 alternative hypothesis: true difference in means is not equal to 0 95 percent confidence interval: -0.05846366 0.32715331 sample estimates: mean of x mean of y 1.310345 1.176000

After data exploration and preprocessing, we are ready to run the regressions.

Causal effect of emotion on the participants' interest scores

We investigated the causal effect of the intensity of the presenter's smile (covariate *smile*), emotion neutrality (covariate *emot_neutral*), and sadness (covariate *emot_sadness*) on participants' interest levels. Here we made an assumption that the presenter's smile will make participants become more interested in the video content. Also, we assumed that if a presenter is emotionless or displayed a negative facial expression, participants will be likely to lose interest and find the video boring. To test the causal relationship in the first assumption, we firstly run a plain OLS regression:

```
# OLS estimate effect of smile on self_interest
pSmile <- plm(self_interest ~ median_smile
              + factor(demo_industry) + factor(demo_age) + factor(demo_gender) + factor(demo_race)
    + factor(demo_education)
              + factor(demo_income) + factor(demo_employment) + factor(demo_country),
      data = ParticipantDataWithVideo,
      index=c("participant_id"),
      model="pooling")
```

Here *median_smile* is a newly constructed covariant that measures the median smile intensity for the duration of a video, and *ParticipantDataWithVideo* is a joint table from ParticipantData and VideoData (See Appendix). Specifically, we used the *plm* package to fit panel data models. In this case, we use *self_interest* as the dependent variable and *median_smile* as the predictor variable. We also added 8 dummy variables (i.e. *demo_industry*, *demo_age*, *demo_gender*, *demo_race*, *demo_education*, *demo_income*, *demo_employment*, *demo_country*) to account for the effects of various categorical variables on participants' interest levels. The model is a "pooling" model, which uses clustered standard errors to ensure observations are independent and improve the validity of causal inference.

Similarly, to probe the causal effect of emotion neutrality on participants' interest in videos, we run the following regressions that includes the same set of covariates for the pooling model. *median_neutral* and *median_sadness* measure the median level of emotion neutrality and negativity for the duration of a video (screenshot omitted due to page limit).

Then we incorporated heterogeneous effects into our regression and ran the regressions on smile and emotion neutrality again.

```
# Heterogeneous: gender & age & education level
phGender_s <- plm(self_interest ~ median_smile
              + I(gender_group) + median_smile:I(gender_group)
        + factor(demo_industry) + factor(demo_age) + factor(demo_gender) + factor(demo_race)
              + factor(demo_education)
              + factor(demo_income) + factor(demo_employment) + factor(demo_country),
      data = ParticipantDataWithVideo,
      index=c("participant_id"),
      model="pooling")
```

Here the independent variables include *median_smile*, *I(gender_group)*, and the interactions between *median_smile* and *I(gender_group)*, as well as the above-mentioned categorical variables. This will allow the model to estimate separate coefficients for each gender/age/education group for smile intensity, allowing for heterogeneous effects of the interest score on the smile levels across groups.

Similar code can be used to obtain the causal effect of emotion neutrality and negativity for heterogeneous groups (screenshot omitted due to page limit).

Causal effect of emotion on the participants' post-quiz scores

For this experiment we are also finding the causal effect of the emotion on the post-quiz score of the participant. Our hypothesis to run this regression was to check if the intensity of the smile is higher, the participants will be more interested in watching the video leading to a high post-quiz score. On the contrary, the higher the sadness intensity is, the less focused the participants will be and the lower the score they will get. Similar to the interest level regressions, we are using the median of the emotions to represent the emotion of the video. Moreover, to truly find the causal effect of the presenter's sadness level, we have also included the pre-quiz score (covariate *correct_pre_quiz*) and the industry the participant studies or works in (covariate *demo_industry*) in the regression. We believe that the two fields could represent the level of understanding the participant has about A/B testing prior to watching the video and this will also affect the post-quiz score.

```
pSmile <- plm(correct_post_quiz ~ median_smile
            + correct_pre_quiz + factor(demo_industry),
      data = ParticipantDataWithVideo,
      index=c("participant_id"),
      model="pooling")
```

Additionally, we also ran the heterogeneous causal effect on gender (covariate *gender_group*), age (covariate *age_group*), and education level (covariate *education_group*). We believe that groups of people with different traits and experiences may react differently to online learning materials.

```
phGender <- plm(correct_post_quiz ~ median_anger
           + I(gender_group) + median_anger:I(gender_group)
           + correct_pre_quiz + factor(demo_industry),
      data = ParticipantDataWithVideo,
      index=c("participant_id"),
      model="pooling")
```

Results Obtained

Causal effect of emotion on the participants' interest scores

In the first regression, we hypothesized that higher smile intensity may lead to higher participants' interest in the video content and higher emotion neutrality or negativity may result in lower participants' interest levels. For plain OLS, the result we got is not statistically significant. Therefore, we cannot say establish causal inferences for these hypotheses.

	Dependent variable:		
	self_interest		
	(1)	(2)	(3)
median_smile	0.937		
	(0.668)		
median_neutral		-0.815	
		(0.619)	
median_sadness			-10.897
			(7.950)
Constant	3.123**	3.969**	3.548**
	(1.535)	(1.570)	(1.520)
Observations	241	241	241
R2	0.375	0.374	0.374
Adjusted R2	0.090	0.089	0.090
F Statistic (df = 75; 165)	1.318*	1.313*	1.317*
Note:	*p<0.1; **p<0.05; ***p<0.01		

We also did not see statistically significant results in either *smile*, *emot_neutral*, or *emot_sadness* after accounting for gender, age, and education levels as our heterogeneous variables. Since heterogeneous effect measures causal effect that varies across different groups or subgroups within the data, no heterogeneous effect found means that the effect of participants' interest levels is the same across all groups or subgroups within the data. In other words, the relationship between interest scores and smile/emotion neutrality/emotion negativity is the same for all gender, age, and education groups of participants in our obtained dataset.

	Dependent variable:		
	self_interest		
	(1)	(2)	(3)
median_smile	1.157	0.748	0.482
	(1.026)	(0.920)	(0.887)
I(gender_group)	0.072		
	(0.279)		
I(age_group)		-0.424	
		(0.899)	
I(education_group)			0.797
			(0.932)
median_smile:I(gender_group)	-0.372		
	(1.311)		
median_smile:I(age_group)		0.409	
		(1.367)	
median_smile:I(education_group)			1.018
			(1.303)
Constant	3.007*	3.132**	3.186**
	(1.553)	(1.539)	(1.539)
Observations	241	241	241
R2	0.375	0.375	0.377
Adjusted R2	0.085	0.085	0.088
F Statistic (df = 76; 164)	1.295*	1.295*	1.306*
Note:	*p<0.1; **p<0.05; ***p<0.01		

	Dependent variable:		
	self_interest		
	(1)	(2)	(3)
median_neutral	-1.027	-0.340	-0.445
	(0.961)	(0.862)	(0.858)
I(gender_group)	-0.271		
	(1.110)		
I(age_group)		0.495	
		(1.398)	
I(education_group)			1.542
			(1.369)
median_neutral:I(gender_group)	0.358		
	(1.241)		
median_neutral:I(age_group)		-1.003	
		(1.266)	
median_neutral:I(education_group)			-0.772
			(1.236)
Constant	4.067**	3.489**	3.668**
	(1.642)	(1.685)	(1.646)
Observations	241	241	241
R2	0.374	0.376	0.375
Adjusted R2	0.084	0.087	0.086
F Statistic (df = 76; 164)	1.290*	1.301*	1.296*
Note:	*p<0.1; **p<0.05; ***p<0.01		

	Dependent variable:		
	self_interest		
	(1)	(2)	(3)
median_sadness	-8.746	-11.306	-5.863
	(12.757)	(12.133)	(15.094)
I(gender_group)	0.103		
	(0.275)		
I(age_group)		-0.324	
		(0.894)	
I(education_group)			0.819
			(0.918)
median_sadness:I(gender_group)	-3.480		
	(16.114)		
median_sadness:I(age_group)		0.717	
		(16.013)	
median_sadness:I(education_group)			-6.969
			(17.745)
Constant	3.464**	3.545**	3.584**
	(1.516)	(1.526)	(1.527)
Observations	241	241	241
R2	0.375	0.374	0.375
Adjusted R2	0.085	0.084	0.085
F Statistic (df = 76; 164)	1.292*	1.291*	1.295*
Note:	*p<0.1; **p<0.05; ***p<0.01		

Causal effect of emotion on the participants' post-quiz scores

In the second regression, we tested the hypothesis that whether high intensity of smile leads to a high post-quiz score and neutral/negative emotion leads to a low post-quiz score. From the result, we could see that although the coefficient of smile is positive and the coefficients of neutral, and sadness are negative, they are not statistically significant, thus, could be treated as zero. This implies that the emotion of the presenter has no impact on the learning of the participants.

	Dependent variable:		
	correct_post_quiz		
	(1)	(2)	(3)
median_smile	0.936		
	(0.597)		
median_neutral		-0.814	
		(0.568)	
median_sadness			-2.294
			(6.920)
correct_pre_quiz	1.181***	1.177***	1.172***
	(0.145)	(0.145)	(0.146)
Constant	2.425***	3.223***	2.526***
	(0.436)	(0.663)	(0.440)
Observations	241	241	241
R2	0.350	0.349	0.343
Adjusted R2	0.275	0.273	0.267
F Statistic (df = 25; 215)	4.634***	4.609***	4.491***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Additionally, we also calculated the heterogeneous causal effect on gender (covariate *demo_gender*), age (covariate *demo_age*), and education level (covariate *demo_education*). We could see that all the coefficients related to the causal effect of the emotion of the presenter are statistically insignificant. Hence, we cannot conclude that the emotion of the presenter leads to an increase or decrease in the post-quiz score.

	Dependent variable:		
	correct_post_quiz		
	(1)	(2)	(3)
median_smile	1.223	0.639	0.923
	(0.938)	(0.867)	(0.798)
I(gender_group)	0.042		
	(0.239)		
I(age_group)		-0.394	
		(0.241)	
I(education_group)			-0.100
			(0.237)
correct_pre_quiz	1.179***	1.178***	1.174***
	(0.146)	(0.145)	(0.147)
median_smile:I(gender_group)	-0.486		
	(1.220)		
median_smile:I(age_group)		0.432	
		(1.239)	
median_smile:I(education_group)			-0.030
			(1.209)
Constant	2.399***	2.647***	2.481***
	(0.460)	(0.457)	(0.455)
Observations	241	241	241
R2	0.351	0.358	0.351
Adjusted R2	0.268	0.277	0.269
F Statistic (df = 27; 213)	4.260***	4.409***	4.264***
Note:	*p<0.1; **p<0.05; ***p<0.01		

	Dependent variable:		
	correct_post_quiz		
	(1)	(2)	(3)
median_neutral	-1.293	-0.292	-0.724
	(0.889)	(0.828)	(0.776)
I(gender_group)	-0.711		
	(1.042)		
I(age_group)		0.408	
		(1.059)	
I(education_group)			0.018
			(1.024)
correct_pre_quiz	1.173***	1.168***	1.168***
	(0.146)	(0.145)	(0.147)
median_neutral:I(gender_group)	0.816		
	(1.159)		
median_neutral:I(age_group)		-0.882	
		(1.180)	
median_neutral:I(education_group)			-0.142
			(1.147)
Constant	3.638***	2.971***	3.201***
	(0.903)	(0.839)	(0.808)
Observations	241	241	241
R2	0.350	0.359	0.350
Adjusted R2	0.268	0.277	0.267
F Statistic (df = 27; 213)	4.256***	4.413***	4.243***
Note:	*p<0.1; **p<0.05; ***p<0.01		

	Dependent variable:		
	correct_post_quiz		
	(1)	(2)	(3)
median_sadness	-6.610	-7.384	3.799
	(11.475)	(11.187)	(11.879)
I(gender_group)	-0.036		
	(0.245)		
I(age_group)		-0.454*	
		(0.248)	
I(education_group)			-0.066
			(0.241)
correct_pre_quiz	1.176***	1.172***	1.175***
	(0.147)	(0.145)	(0.148)
median_sadness:I(gender_group)	6.876		
	(14.615)		
median_sadness:I(age_group)		9.285	
		(14.417)	
median_sadness:I(education_group)			-8.795
			(14.848)
Constant	2.544***	2.755***	2.542***
	(0.463)	(0.456)	(0.462)
Observations	241	241	241
R2	0.344	0.353	0.345
Adjusted R2	0.261	0.271	0.262
F Statistic (df = 27; 213)	4.132***	4.311***	4.159***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Conclusion

Upon running the above-mentioned four regressions on our dataset, we can see that the causal effect of presenters' emotions on interest levels and learning outcomes is not statistically significant for our data.

However, this conclusion is only limited to our small data generated over a period of nearly 2 weeks. It is highly likely that the above regressions didn't indicate a causal relationship because the effect is very minute to be observed over a small dataset as ours.

To truly understand if there's a causal relationship, we suggest collecting more data, over a longer period of time.

Appendix

```r
# summarize video data
VideoDataSummary <- VideoData %>%
          group_by(video_id) %>%
          summarize(median_smile = median(smile),
          median_neutral = median(emot_neutral))
```

```r
# combine video data with participant data
ParticipantDataWithVideo <- inner_join(x = ParticipantData, y = VideoDataSummary, by = "video_id")
```

```r
# divide to two group using threshold
ParticipantData <- ParticipantData %>%
  mutate(age_group = if_else(demo_age == "a", 0, 1))
ParticipantData <- ParticipantData %>%
  mutate(gender_group = if_else(demo_gender == "b", 0, 1))
ParticipantData <- ParticipantData %>%
  mutate(education_group = if_else(demo_education <= "d", 0, 1))
```

Code screenshot backup

```
pNeutral <- plm(self_interest ~ median_neutral
                + factor(demo_industry) + factor(demo_age) + factor(demo_gender) + factor(demo_race)
                + factor(demo_education)
                + factor(demo_income) + factor(demo_employment) + factor(demo_country),
                data = ParticipantDataWithVideo,
                index=c("participant_id"),
                model="pooling")


pSad <- plm(self_interest ~ median_sadness
            +   factor(demo_industry) + factor (demo_age) + factor(demo_gender)
            + factor (demo_race) + factor(demo_education) + factor(demo_income)+
              factor (demo_employment) + factor(demo_country),
            data = ParticipantDataWithVideo,
            index=c("participant_id"),
            model="pooling")


pAnger <- plm(self_interest ~ median_anger
              +factor(demo_industry) + factor (demo_age) + factor(demo_gender)
             + factor (demo_race) + factor(demo_education) + factor(demo_income) +
             factor (demo_employment) + factor(demo_country),
              data = ParticipantDataWithVideo,
              index=c("participant_id"),
              model="pooling")


phGender_en <- plm(self_interest ~ median_neutral
                   + I(gender_group) + median_neutral:I(gender_group)
                   + factor(demo_industry) + factor(demo_age) + factor(demo_gender) + factor(demo_race)
                   + factor(demo_education)
                   + factor(demo_income) + factor(demo_employment) + factor(demo_country),
                   data = ParticipantDataWithVideo,
                   index=c("participant_id"),
                   model="pooling")

phAge_en <- plm(self_interest ~ median_neutral
                + I(age_group) + median_neutral:I(age_group)
                + factor(demo_industry) + factor(demo_age) + factor(demo_gender) + factor(demo_race)
                + factor(demo_education)
                + factor(demo_income) + factor(demo_employment) + factor(demo_country),
                data = ParticipantDataWithVideo,
                index=c("participant_id"),
                model="pooling")

phEducation_en <- plm(self_interest ~ median_neutral
                      + I(education_group) + median_neutral:I(education_group)
                      + factor(demo_industry) + factor(demo_age) + factor(demo_gender) + factor(demo_race)
                      + factor(demo_education)
                      + factor(demo_income) + factor(demo_employment) + factor(demo_country),
                      data = ParticipantDataWithVideo,
                      index=c("participant_id"),
                      model="pooling")
```

```
phGender <- plm(self_interest ~ median_sadness
             + I(gender_group) + median_sadness:I(gender_group)
             +   factor(demo_industry) + factor (demo_age) + factor(demo_gender)
             + factor (demo_race) + factor(demo_education) + factor(demo_income)+
               factor (demo_employment) + factor(demo_country),
     data = ParticipantDataWithVideo,
     index=c("participant_id"),
     model="pooling")

phAge <- plm(self_interest ~ median_sadness
             + I(age_group) + median_sadness:I(age_group)
             +   factor(demo_industry) + factor (demo_age) + factor(demo_gender)
             + factor (demo_race) + factor(demo_education) + factor(demo_income)+
               factor (demo_employment) + factor(demo_country),
     data = ParticipantDataWithVideo,
     index=c("participant_id"),
     model="pooling")

phEducation <- plm(self_interest ~ median_sadness
             + I(education_group) + median_sadness:I(education_group)
             +   factor(demo_industry) + factor (demo_age) + factor(demo_gender)
             + factor (demo_race) + factor(demo_education) + factor(demo_income)+
               factor (demo_employment) + factor(demo_country),
     data = ParticipantDataWithVideo,
     index=c("participant_id"),
     model="pooling")
```